Evolutionary Algorithms for Modelling Interregional Transport Flows

Reggiani, A; Nijkamp, P.; Sabella, E.

published in
Regional Competition
2000

document version
Publisher's PDF, also known as Version of record

38TH CONGRESS OF THE
EUROPEAN REGIONAL SCIENCE ASSOCIATION
28 AUGUST- 1 SEPTEMBER 1998 IN VIENNA

EVOLUTIONARY ALGORITHMS: OVERVIEW AND APPLICATIONS TO EUROPEAN TRANSPORT

Aura Reggiani[*] , Peter Nijkamp[**] and Enrico Sabella[*,]**

[*] Department of Economics, Faculty of Statistics, Università di Bologna, Piazza Scaravilli, 2, 40126 Bologna, Italy - e-mail: reggiani@economia.unibo.it; sabel00@economia.unibo.it

[**] Department of Spatial Economics, Faculty of Economics, Free University, De Boelelaan 1105, 1081 HV - Amsterdam, The Netherlands - e-mail: pnijkamp@econ.vu.nl; esabella@econ.vu.nl

ABSTRACT

This paper seeks to analyse the research potential of Evolutionary Algorithms (EAs) with a view to their applicability in analysing the space-economy.

For this purpose the first part of the paper will be devoted to an overview and illustration of EAs, also in comparison with other recent tools emerging from bio-computing, like Neural Networks (NNs).

The second part of the paper will focus on empirical applications to the analysis and forecasting of European freight transport flows (at a regional level). In this context, also a merger of EAs and NNs in a form of a hybrid model will be developed. The results stemming from such an integrated approach combining EAs with NNs will be compared with those from conventional methodologies (like logit models) and ‘standard’ NN models. We will analyse the sensitivity of various modelling results by presenting different environmental policy scenarios on European transport. These empirical experiments serve to highlight the advantages and limitations of these approaches from both a methodological and empirical viewpoint.

1. INTRODUCTION

The analysis of complex networks has in recent years become an important research issue in spatial economics and regional science. An important methodological step forward in this context has been offered by synergetic theory and the relative dynamics concept of network evolution (see, for a review, Nijkamp and Reggiani 1998). These concepts have intensified the search for *universal principles* driving non-linear dynamic systems with a particular interest in methodological underpinnings and instruments. In modern research in this field a new class of models, based on bio-computing and artificial intelligence, has come recently to the fore. These new approaches demonstrated a high potential in modelling high-dimensional spatial networks.

The aim of this paper is now to investigate these new tools in the context of a spatial complex network, i.e., the European freight transport network. For this purpose two specific neuro-computing approaches, viz. neural networks and evolutionary algorithms, will be explored and also combined in order to model the European freight transport flows. In addition, also a logit approach will be considered in order to perform a comparative sensitivity analysis among these various techniques.

The present paper is organised as follows. Section 2 highlights some recent contributions that have a relevance for the spatial sciences, like neuro-computing models and evolutionary algorithms. Next, the paper will illustrate in detail the potential of evolutionary algorithms, particularly genetic algorithms, in the context of complex network. Section 4 will then explore the potential and applicability of our 'hybrid' approach based on evolutionary algorithms and neural network analysis. This approach will be applied to modelling and forecasting experiments of European freight transport flows. The paper ends with some suggestions for future research (Section 5).

2. THE PATHWAY TO NEUROCOMPUTING MODELS

2.1 Neural Network Models

In recent years neural networks[1] have become popular tools in analysing complex systems. Also in the social sciences they have gained much popularity. Complex choice problems are increasingly analysed on the basis of a similarity with the functions and actions of human brains. This new approach is also reflected in concepts like bio-computing and artificial intelligence. The recent scientific literature has witnessed much interest in neural networks (NNs) as alternative models of information processing (see, for a review, Reggiani *et al.*, 1998a). Neural network approaches are different from conventional model in that they are able to generalise from experience, without fixing – *a priori* – any behavioural rule/model among underlying behavioural variables (see for overviews *inter alia*, Maren *et al.*, 1990 , and Rumelhart *et al.,* 1986). A great variety of applications of NNs can nowadays be found in many disciplines. In geography and regional science this approach has also found many applications, e.g. in the area of transport and spatial-economic interactions (see, for a review, Himanen *et al.*, 1998, and Reggiani *et al.*, 1998a). In this approach it is necessary to adopt tools that are able to map out connectivity, communication, adaptivity, control and prediction patterns (see also Nijkamp *et al.*, 1997). We will give here a very concise introduction to NNs.

In the standard literature on NNs, the structure of NNs is generally represented by logical units ('neurons') connected by channels of communication ('synapses') which intercompute independently, since each unit cooperates in the transmission of information by means of a different 'weight[2]'. This differentiation in the weights thus corresponds to different values in the synapses. The above phenomenon takes place in particular during the phase of 'learning' in order to allow adaptation to new conditions. In fact, just like cerebral behaviour, NNs are also able to recognise patterns which they have never observed before. This characteristic of 'generalising[3]' identifies the behaviour of the system as 'intelligent'. In other words, since 'real' events never repeat themselves in the same manner, intelligent systems are able to identify, by means of past experience, the continuity and similarity of such events, and hence they offer the possibility of predicting future events (in terms of plausible values of variables).

In class of Artificial Intelligence approaches, NNs are able to elaborate and create information by means of Parallel Distributed Processing systems. This is an important feature of NNs, since massive parallellism provides, on the one hand, the possibility of significantly increasing computer speed (see Kosko, 1992) and, on the other hand, provides a great 'fault tolerance' (since inter-connection between units is essentially local).

NNs can be considered as non-linear dynamic systems with many freedom degrees as well as 'free' models of estimation (see Kosko, 1992). Consequently, the common element in the above definitions is the concept of 'freedom'; in other words, there is 'free biological behaviour' within NN which cannot be

[1] Sections 2 and 3 are largely based on Reggiani *et al*. (1998c)
[2] Here weight is a real number assigned to a connection between two units.
[3] 'Generalising' is the capacity of a system to create new patterns in accordance with previously studied examples.

subjected to any mathematical model (usually creating logical bounds between output and input). Thus, in contrast to the necessity to programme computers (which requires knowledge of the mathematical model which represents the reality concerned), NNs are trained; that is, they learn from a set of 'examples' with input and output data.

NNs are particularly suitable in a forecasting context**,** given their ability to generalise. It should be noted that this peculiarity strictly depends on both the chosen training set and on the architectural configuration of the network (number of hidden levels, number of units on these levels, etc.) (see e.g. Fischer and Gopal, 1994). Details on NN structures and typologies can be found in Nijkamp and Reggiani (1998), Nijkamp *et al.* (1997), and Reggiani *et al.* (1998a). Several applications on high-dimensional complex networks, like the Italian passenger transport network (Nijkamp *et al*., 1996) or the European freight transport networks (Reggiani *et al.*, 1998b), showed a good performance of NNs. However, NNs are still not easily interpretable from a behavioural viewpoint, even though recent results show a compatibility between NNs and binary logit models emerging from micro-economic theory (Schintler and Olurotimi, 1998).

In the context of the present interest in complex network modelling, a great potential is also offered by evolutionary computations, particularly evolutionary algorithms, that are able to find optimal patterns by means of the mechanism of natural selection and natural genetics. This new interesting tool will now first be dealt with in a concise manner.

2.2 Evolutionary Algorithms

In recent years we have seen a great variety of new contributions to evolutionary thinking in spatial economics. In the same vein also several ecologically-based model experiments have been developed, which have stimulated the use of evolutionary algorithms (EAs) in social science research (including geography and regional science).

In the recent literature, EA has become a generic term referring to computer-based problem solving systems which utilise computational models of evolutionary processes and structures as key elements in their design, specification and implementation. In other words, EAs are – usually stochastic – search methods of human behaviour that aim to mimic the metaphor of natural biological evolution in social science research issues. They normally operate on a population of potential solutions to choice problems by applying the principle of survival of the fittest to produce increasingly better approximations to a final equilibrium solution. For each relevant generation of solution types, a new set of solution approximations is created by means of a selection process of individual approximations according to their level of 'fitness' in the problem domain and by combining them together by means of operators borrowed from natural genetics.

The above mentioned repetitive process leads to the evolution of sets of individual solutions that are better suited to their choice environment than the individuals they were originating from, by means of a process of natural adaptation. EAs try to simulate three main characteristics generally belonging to a natural dynamic system: (a) adaptivity; (b) stochasticity; (c) parallelism (see Colorni *et al.*, 1994). The first property refers to the possibility – for a system – of modifying its solution results by means of feedback effects; the second one allows the system to find ‘good’ solutions in a short time, by using property (a); and the third one outlines the possibility of using high parallel computer power as a consequence of property (b). In conclusion, EAs are able to map out a fundamental characteristic of networks in natural systems, i.e., the synergy effect, characterising also the functioning and operation of socio-economic and spatial networks (see Nijkamp and Reggiani, 1996). We will explore the possibilities of this new tool in greater detail in the next section

3. ANALYSIS OF COMPLEX DYNAMIC NETWORKS BY MEANS OF EVOLUTIONARY ALGORITHMS

3.1 Prologue

In the recent years, much interest has arisen in EA applications. EAs are based on the imitation of processes which can be found in the natural evolution of species. Their origin, as mentioned before, can be found in biology rather than in computer sciences. This concept of evolution originates from dynamic biology and population dynamics and is implicitly or explicitly governed by chromosomes[4]: organic information carriers which contain the exact characteristics of a living being. The living being can be ‘constructed’ by decoding its chromosomes. The way this is done is not yet known exactly, but the following features seem to be important (see also Goldberg, 1989):

– evolution is a process working on chromosomes instead of the living beings they represent.
– natural selection is the dynamic relationship between chromosome; in other words, it is the successful performance of their decoded structure which will more often reproduce.
– evolution occurs while reproducing. Mutation can, for instance, be the reason why chromosomes of the children sometimes differ from the ones of their parents in certain places. The chromosomes of the parents are combined in a certain way so as to create new and different chromosomes for the children.
– biologic evolution has no memory. All it knows about individuals that perform well in their

[4]For a definition of the biological terminology we refer to Mitchell (1996, p.5) : “All living organisms consist of cells, and each cell contains the same set of one or more *chromosomes* ─ string of DNA ─ that serve as a ‚blueprint’ for the organism. A chromosome can be conceptually divided into *genes* ─ functional blocks of DNA ─ each of which encodes a particular protein. Very roughly, one can think of a gene as encoding a trait, such as eye color. The different possible ‘settings’ for a trait (e.g., blue, brown, hazel) are called *alleles*. Each gene is located at a particular *locus* (position) on the chromosome”.

environment is stored in the set of chromosomes of the present individuals and in the way these chromosomes are encoded.

It also noteworthy that EAs work on populations of individuals represented by chromosomes instead of single solutions[5].

In an EA context, computational algorithm a number of individuals (the 'population') is randomly initialised (initial generation) in order to start a suitable. The objective function is then evaluated for these individuals. If the optimisation criteria are not met, the creation of a new generation starts. Individuals are then selected according to their fitness (i.e., contribution to the optimal solution) for the production of offspring[6]. All offspring will be mutated with a certain probability. The fitness of the offspring can then be computed. The offspring are next inserted into the population replacing the parents, thus producing a new generation. This cycle continues until the optimisation criteria are met.

The above mentioned EA structure – which concerns a single population – performs well on a broad class of problems. This process has a similarity to many real-world dynamic choice processes. However, better results can be obtained by introducing many populations (multipopulations). Each micro-population is then called subpopulation. Every subpopulation evolves independently for a few generations (like the single population EA); next, one or more individuals are exchanged between the subpopulations. Consequently, the multipopulation EA models the evolution of a species in a way more similar to nature than the single population EA. In Subsection 3.2 we will illustrate one of the most relevant classes of models belonging to EAs, viz. genetic algorithms.

3.2 Genetic Algorithms

Genetic algorithms (GAs) are a new class of evolutionary algorithms and may be regarded as computational models inspired by population genetics. In scientific research, GAs have mainly been used as function optimisers. They have been proven to be effective global optimisation tools, especially for multimodal and non-continuous functions (see De Jong, 1975). Their strength is essentially due to their ability to update an entire population of possible solutions during each iteration round; this allows for a parallel investigation of the search space (see Holland, 1975, and Bertoni and Dorigo, 1992).

We will now offer a concise introduction to the GA computational paradigm and to its most successful parallel version, based on the work by Dorigo and Maniezzo (1992) and Maniezzo (1994). According to these authors, a GA evolves as a multiset of elements, called *population of individuals*. Each individual Xi ($i=1.....n$) of the population X represents a trial solution of the problem to be solved.

---

[5]In EAs, the term 'chromosome' refers typically to a candidate solution to a problem, often encoded as a bit string.
[6]Offspring can be defined as the result of reproduction. In biological evolution, it is usually referred to as the child.

Individuals are usually represented by strings of variables, each element of which is called a *gene*. The value of a gene is called its *allelic value*, and it varies over a range on a set which is usually restricted to {0,1}, and which is usually continuous and even structured.

A GA is able to of maximise a given *fitness function* (FF) computed on each individual of the population. If the problem is to minimise a given *objective function*, then it is necessary to identify and map out increasing FF values; this can be achieved by a monotonically decreasing function. The basic structure of Gas can be found in Reggiani *et al*. (1998c).

The space to be researched in GAs is usually encoded as a binary string. An initially random population of such strings is maintained. During each iteration round, the performance of each individual (solution) is evaluated. A new generation of individuals is then produced by applying a set of *genetic operators* to selected individuals from the previous generation. In the work of Maniezzo (1994, p. 40) the commonly used operators are described as follows:

i) Reproduction (selection): This operator produces a new population, $Xr(t)$, extracted by means of a repetition of individuals from the old population, $X(t)$. The extraction can be carried out in several ways. One of the most commonly used methods is the *roulette wheel selection* (see Goldberg, 1989), where individuals are extracted with a probability following a Monte Carlo procedure. The extraction probability $pr(xi)$ of each individual xi is proportional to its fitness $FF(xi)$ as a ratio with respect to the average fitness of all individuals in $X(t)$:

$$pr(xi) = FF(xi) / \sum_{i=0}^{n} FF(xi)$$

ii) Crossover: This operator is applied in a probability setting, where the crossover probability is a system parameter, pc. In order to apply the standard crossover operator (in fact, in the literature several variants have been proposed), the individuals of the population are randomly paired. Each pair is then recombined, choosing one point in accordance with a uniformly distributed probability over the length of the individual string (*parents*) and cutting them into two parts, accordingly. The new individuals (*offspring*) are formed by the juxtaposition of the first part of one parent and the last part of the other parent.

iii) Mutation: The standard mutation operator modifies each allele of each individual of the population with a certain probability, where the mutation probability is a system parameter, pm. Usually, the new allelic value is randomly chosen with a uniform probability distribution.

iv) Local Search: The necessity of this operator for optimisation problems is still under debate. Local search is usually a simple gradient-descent heuristic that carries each solution to a local optimum. The rationale behind this operator has been first advocated by Muhlenbein (see Muhlenbein, 1989), suggesting that search in the space of local optima is much more effective than search in the whole solution space.

Recent results on the Quadratic Assignment problem and on the Time Table problems seem to support this hypothesis (see Colorni *et al.*, 1992a, 1992b).

Crossover is generally considered to be the principal search mechanism, with mutation relegated to a background operator whose exclusive role is to maintain diversity in the population and to ensure that every point in the search space has some chance of being visited. By iterating the processes of selection, recombination and mutation, the population accumulates information about the distribution of fitness in the search space. One of the regions in which GAs perform quite well is optimisation. GAs are normally very *robust,* which means that they operate on a broad range of problems.

Given these characteristics of GAs, as well as their performance in existing applications (see, for a review, Colorni *et al.*,1994), it seems now worthwhile to explore this tool also in new field of application, like, for example, the modal split problem in a complex high-dimensional network (e.g. the European freight transport network). In previous works by the authors (Nijkamp and Reggiani, 1998; Reggiani *et al.*, 1998b, 1998c), this problem has been explored by means a comparative analysis between logit and NN models. The results were quite interesting; sometimes rather significant differences between these two categories of models appeared to emerge.

The present paper is a follow-up of these previous research endeavours, since – in addition to logit and NN models – we aim to investigate here – for the same European spatial network – the 'power' of EAs, by deploying a hybrid model on the basis of GAs combined with NNs. Various results from our empirical analysis will be presented in the next section.

4. EVOLUTIONARY NEURAL NETWORK MODELLING INTERREGIONAL EUROPEAN FREIGHT TRANSPORT MODELLING

4.1 Introduction

In the present section we will focus our attention on the performance of EAs discussed in the previous sections in order to highlight the potentials/limitations of these new approaches. We will consider – as a case study – the European freight transport network with reference to the modal split problem between rail and road transport modes. In particular, different NN models will be investigated and compared also in combination with GAs. The class of NN models adopted here comprises 2 categories:

A: A Neural Network model using a backpropagation algorithm for the learning procedure [NN(BP)].

B: A Neural Network model using a genetic algorithm for the learning procedure [NN (GA)].

These 2 categories of neuro-computing models will be compared with a conventional choice model, often used in transportation research, viz. the logit model (see, for an overview, Ben Akiva and Lerman, 1985):

C: A Logit model using a Newton-Raphson algorithm for the calibration procedure.

Finally, a sensitivity analysis will be carried out in order to investigate the results of the three models A, B and C under different policy scenarios of freight flows. On the one hand, our aim is to present a manageable tool for modelling like the combined logit and NN approach. On the other hand, we wish to explore the suitability of this parallel approach also in the context of forecasting analysis.

4.2 The data

The data set[7] contains the freight flows and the attributes related to each link between 108 European regions[8] for the year 1986. The attributes considered are *'distance'*, '*time'* and '*cost'* between each link (ij) with reference to each transport mode. Each observation of the data set pertains to variables related to each link (ij). Furthermore, the flow distribution in the matrices concerned refers to one particular kind of goods, viz. the food sector.

Since 108 areas have been considered, the data set should ideally contain 11664 observations (according to the previous remarks on our observations). However, our data set contains actually 4409 observations because of the following considerations (by analysing the data set):

- the intra-area freight flows are zero;
- for each link, only the transport movements in one direction $i \rightarrow j$ have been considered;
- only the links where the flows and the attributes (of both road and rail) are different from zero have been considered (i.e., empty cells are excluded).

The data set has been randomly subdivided into three sub-sets:

- a *training set* containing 2992 observations, i.e. about 68% of the data-set;
- a *cross-validation set* containing 447 observations, i.e. about 10% of the data-set;
- a *test set* containing 970 observations, i.e. about 22% of the data-set.

For the analysis of the logit model, the adopted calibration set – used for estimating unknown parameters in the utility function – also comprehends the training set combined with the cross-validation set.

4.3 Comparative analysis among the models adopted

In this subsection, the spatial forecasting performance of the three alternative chosen approaches (models A, B and C) will be compared and evaluated, on the basis of the calibration/learning procedure.

[7] The data set has been kindly provided by NEA Transport Research and Training, Rijswijk.

By using the test set, which was not used for the learning procedure, we have employed the models A, B and C in our procedure to predict the freight flows for link (ij). This performance has been evaluated using statistical indicators[9] (ARV, R^2, MSE, PAME).

Table 1. Comparison of Logit and NN performance

	ARV	**R^2**	**MSE**	**PAME**
A) NN(BP)	0.143	0.9523	0.0398	12.34 %
B) NN(GA)	0.115	0.9630	0.0386	11,33 %
C) Logit	0.185	0.8352	0.0464	12.93 %

According to the above indicators, the NN model combined with GA for forecasting spatial flows appears to performs slightly better than the other two approaches (see Table 1). It is also evident that there is a 'structural' difference between the two 'typologies' A and B in association with the NN model on the hand and the logit model (model C) on the other.

Next, an extrapolation of estimated data against the real data from the 'data-set' is carried out with reference to some European regions (inflows to Europe/outflows from Europe) in order to better evaluate the performance of our models (see Tables 2-7). In this context, we have focused on a subset of Europe: the peripheral/core regions in Europe (see Figure 1) to highlight empirical differences among these regions under different environmental policy scenarios. More precisely, Tables 2 and 3 illustrate the estimated/real flows for the outflows, from the peripheral and core regions, respectively, towards the rest of Europe. Tables 5 and 6 display the estimated/real flows for the inflows towards the aforementioned regions from the rest of Europe.

[9] For the definition of the statistical indicators ARV (Average Relative Variance), R^2 (Correlation Coefficient), MSE (Mean Square Error) and MAPE (Mean Absolute Percentage Error), we refer to Reggiani *et al.*, 1998c.

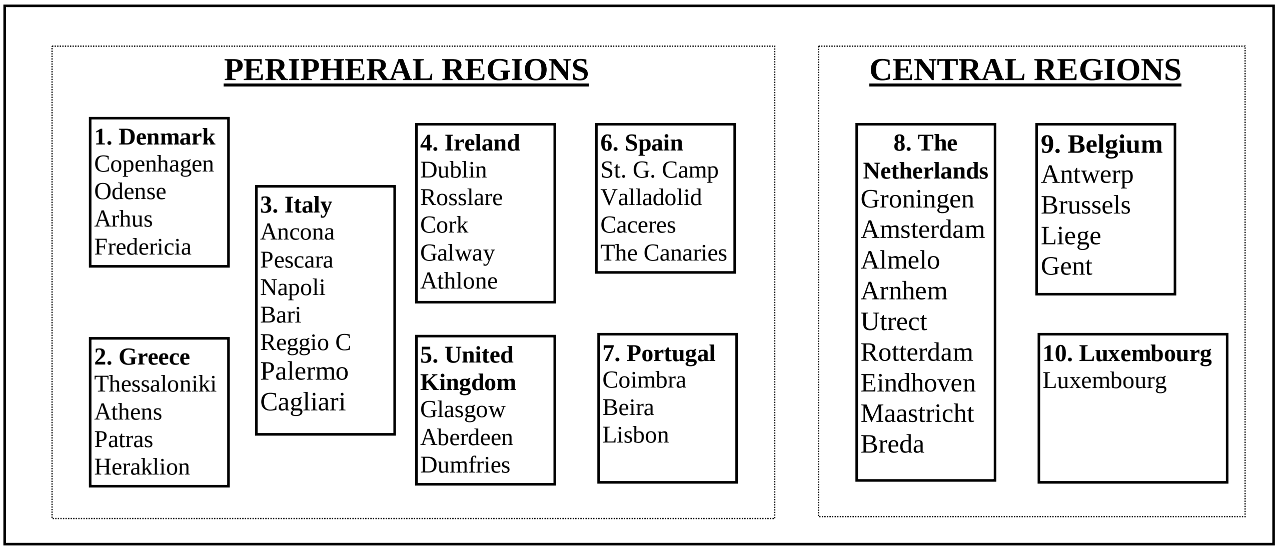


Figure 1. The European regions under consideration

We have also calculated the relative prediction error (see again Tables 2-3 and Tables 5-6) for all the models adopted (defined as the difference between the predicted flow and the real flow as a percentage of the real flow), the mean value of the variations from the real data (M) and the mean value of the absolute variations from the real data (MA) (see Tables 4 and 7). It is evident from Tables 2-7 that the NN model in conjunction with the GA approach (model B) performs better than the others. This result corresponds to our previous findings (see Table 1): in this context it should be noted that models A and C can be considered valid as well, given their ‘good’ statistical outcomes.

Table 2. Transport flows by road from the peripheral regions to the rest of Europe (outflows)

Region	*real flow*	*pred. flow NN(BP)*	*pred. flow. NN(GA)*	*pred. flow Logit*	*error % NN(BP)*	*error % NN(GA)*	*error % Logit*
Denmark							
Copenhagen	143309	157760	154391	157881	10.08	7.73	10.17
Odense	53954	55711	54560	54979	3.26	1.12	1.90
Arhus	127973	128011	125516	128987	0.03	-1.92	0.79
Fredericia	55307	55519	54995	56859	0.38	-0.56	2.81
Total	**380543**	**397001**	**389462**	**398706**	**4.32**	**2.34**	**4.77**
Greece							
Thessaloniki	19322	19467	19586	21382	0.75	1.37	10.66
Athens	25354	28262	26009	31210	11.47	2.58	23.10
Patras	22327	21957	21832	24167	-1.66	-2.22	8.24
Heraklion	18301	17949	17850	19839	-1.92	-2.46	8.40
Total	**85304**	**87635**	**85277**	**96598**	**2.73**	**-0.03**	**13.24**
Italy							
Ancona	872035	851495	870104	795423	-2.36	-0.22	-8.79
Pescara	478693	466085	478820	445893	-2.63	0.03	-6.85
Napoli	617821	595928	617353	588553	-3.54	-0.08	-4.74
Bari	1139009	1094250	1138347	1098769	-3.93	-0.06	-3.53
Reggio C.	57426	55088	57683	56364	-4.07	0.45	-1.85
Palermo	541900	519230	546278	545386	-4.18	0.81	0.64
Cagliari	48207	46631	48500	48492	-3.27	0.61	0.59
Total	**3755091**	**3628707**	**3757085**	**3578880**	**-3.37**	**0.05**	**-4.69**
Ireland							
Dublin	42915	40855	43064	43080	-4.80	0.35	0.38
Rosslare	0	0	0	0	0.00	0.00	0.00
Cork	0	0	0	0	0.00	0.00	0.00
Galway	0	0	0	0	0.00	0.00	0.00
Athlone	0	0	0	0	0.00	0.00	0.00
Total	**42915**	**40855**	**43064**	**43080**	**-4.80**	**0.35**	**0.38**
United Kingdom							
Glasgow	3077718	3031443	3083775	2799452	-1.50	0.20	-9.04
Aberdeen	0	0	0	0	0.00	0.00	0.00
Dumfries	0	0	0	0	0.00	0.00	0.00
Total	**3077718**	**3031443**	**3083775**	**2799452**	**-1.50**	**0.20**	**-9.04**
Spain							
St.G.di Camp	968652	926981	964263	923481	-4.30	-0.45	-4.66
Valladolid	2837399	2775056	2836820	2593247	-2.20	-0.02	-8.60
Caceres	597251	592522	609672	568168	-0.79	2.08	-4.87
The Canaries	0	0	0	0	0.00	0.00	0.00
Total	**4403302**	**4294559**	**4410755**	**4084896**	**-2.47**	**2.06**	**-7.23**
Portugal							
Coimbra	21961	21546	22504	22279	-1.89	2.47	1.45
Beira	20158	19234	20249	20034	-4.58	0.45	-0.62
Lisbon	87620	81668	86362	87845	-6.79	-1.44	0.26
Total	**129739**	**122448**	**129115**	**130158**	**-5.62**	**1.49**	**0.32**

Table 3. Transport flows by road from the core regions to the rest of Europe (outflows)

Region	*real flow*	*pred. flow NN(BP)*	*pred. flow. NN(GA)*	*pred. flow Logit*	*error % NN(BP)*	*error % NN(GA)*	*error % Logit*
The Netherlands							
Groningen	328606	348602	349235	337568	6.09	6.28	2.73
Amsterdam	701562	692485	705001	649653	-1.29	0.49	-7.40
Almelo	186735	183065	188491	180435	-1.97	0.94	-3.37
Arnhem	676355	666599	682798	645846	-1.44	0.95	-4.51
Utrecht	182875	178403	181806	166947	-2.45	-0.58	-8.71
Rotterdam	2321726	2402006	2430904	2220821	3.46	4.70	-4.35
Eindhoven	1243979	1228018	1242764	1152413	-1.28	-0.10	-7.36
Maastricht	553990	541158	550002	499993	-2.32	-0.72	-9.75
Breda	279996	275070	280966	259956	-1.76	0.35	-7.16
Total	**6475824**	**6515406**	**6611967**	**6113632**	**0.61**	**2.10**	**-5.59**
Luxembourg							
Luxembourg	131905	128872	131455	119599	-2.30	-0.34	-9.33
Total	**131905**	**128872**	**131455**	**119599**	**-2.30**	**-0.34**	**-9.33**
Belgium							
Antwerp	1832589	1833654	1866415	1711143	0.06	1.85	-6.63
Brussels	85388	92481	93180	83059	8.31	9.13	-2.73
Liege	173614	175391	179219	166649	1.02	3.23	-4.01
Gent	963656	943952	957921	870673	-2.04	-0.60	-9.65
Total	**3055247**	**3045478**	**3096735**	**2831524**	**-0.32**	**1.36**	**-7.32**

Table 4. The statistical indicators M and MA concerning the results in Tables 2 and 3

Country	*NN(BP) model*		*NN(GA) model*		*Logit model*	
	M	***MA***	*M*	***MA***	*M*	***MA***
Denmark	3.44	**3.44**	1.59	**2.84**	3.92	**3.93**
Greece	2.16	**3.95**	-0.18	**2.16**	12.60	**12.60**
Italy	-3.43	**3.43**	0.22	**0.32**	-3.50	**3.86**
Ireland	-0.96	**0.96**	0.07	**0.07**	0.08	**0.08**
UK	-0.50	**0.50**	0.07	**0.07**	-3.01	**3.01**
Spain	-1.82	**1.82**	0.40	**0.64**	-4.53	**4.53**
Portugal	-4.42	**4.42**	0.50	**1.45**	0.36	**0.77**
Holland	-0.33	**2.45**	1.37	**1.68**	-5.54	**6.15**
Luxembourg	-2.30	**2.30**	-0.34	**0.34**	-9.33	**9.33**
Belgium	1.84	**2.86**	3.40	**3.70**	-5.75	**5.75**

M = mean value of the variations from the real data

MA = mean value of the absolute variations from the real data

Table 5. Transport flows by road from the rest of Europe to the peripheral regions (inflows)

Region	*real flow*	*pred. flow NN(BP)*	*pred. flow. NN(GA)*	*pred. flow Logit*	*error % NN(BP)*	*error % NN(GA)*	*error % Logit*
Denmark							
Copenhagen	101176	102273	102646	102694	1.08	1.45	1.50
Odense	65340	65576	65803	64334	0.36	0.71	-1.54
Arhus	177846	177638	177892	173025	-0.12	0.03	-2.71
Fredericia	283904	285876	285964	272429	0.69	0.73	-4.04
Total	**628266**	**631363**	**632305**	**612482**	**0.49**	**0.64**	**-2.51**
Greece							
Thessaloniki	54446	51577	54569	56198	-5.27	0.23	3.22
Athens	60767	57092	59972	62392	-6.05	-1.31	2.67
Patras	62267	58336	61306	63743	-6.31	-1.54	2.37
Heraklion	62768	59288	62020	65004	-5.54	-1.19	3.56
Total	**240248**	**226293**	**237867**	**247337**	**-5.81**	**-0.99**	**2.95**
Italy							
Ancona	493415	485799	492066	443096	-1.54	-0.27	-10.20
Pescara	593302	577053	593354	555442	-2.74	0.01	-6.38
Napoli	459656	459815	462036	466905	0.03	0.52	1.58
Bari	620101	596534	618674	591725	-3.80	-0.23	-4.58
Reggio C.	36261	34549	36719	37145	-4.72	1.26	2.44
Palermo	333612	316656	334864	335029	-5.08	0.38	0.42
Cagliari	159154	150450	157883	158741	-5.47	-0.80	-0.26
Total	**2695501**	**2620856**	**2695596**	**2588083**	**-2.77**	**0.00**	**-3.99**
Ireland							
Dublin	21861	21358	21602	22540	-2.30	-1.18	3.11
Rosslare	0	0	0	0	0.00	0.00	0.00
Cork	0	0	0	0	0.00	0.00	0.00
Galway	0	0	0	0	0.00	0.00	0.00
Athlone	0	0	0		0.00	0.00	0.00
Total	**21861**	**21358**	**21602**	**22540**	**-2.30**	**-1.18**	**3.11**
United Kingdom							
Glasgow	487752	473037	488317	461230	-3.02	0.12	-5.44
Aberdeen	0	0	0	0	0.00	0.00	0.00
Dumfries	0	0	0	0	0.00	0.00	0.00
Total	**487752**	**473037**	**488317**	**461230**	**-3.02**	**0.12**	**-5.44**
Spain							
St.G.di Camp	250109	248361	252143	251157	-0.70	0.81	0.42
Valladolid	15694	18416	18641	18964	17.34	18.178	20.84
Caceres	133212	130337	133508	124663	-2.16	0.22	-6.42
The Canaries	1663	1505	1602	1662	-9.50	-3.67	-0.06
Total	**400678**	**398619**	**405894**	**396446**	**-0.51**	**1.30**	**-1.06**
Portugal							
Coimbra	18444	19053	19070	19865	3.30	3.39	7.70
Beira	24018	23795	24003	24520	-0.93	-0.06	2.09
Lisbon	31628	31062	31304	31814	-1.79	-1.02	0.59
Total	**74090**	**73910**	**74377**	**76199**	**-0.24**	**0.39**	**2.85**

Table 6. Transport flows by road from the rest of Europe to the core regions (inflows)

Region	*real flow*	*pred. flow NN(BP)*	*pred. flow. NN(GA)*	*pred. flow Logit*	*error % NN(BP)*	*error % NN(GA)*	*error % Logit*
The Netherlands							
Groningen	342596	339262	343853	320882	-0.97	0.37	-6.34
Amsterdam	193554	200409	202186	188456	3.54	4.46	-2.63
Almelo	276011	270623	275677	250186	-1.95	-0.12	-9.36
Arnhem	788554	773722	786535	708090	-1.88	-0.26	-10.20
Utrecht	315826	309023	314114	283615	-2.15	-0.54	-10.20
Rotterdam	583921	632643	620496	605218	8.34	6.26	3.65
Eindhoven	845120	844353	844981	768870	-0.09	-0.02	-9.02
Maastricht	180917	180569	180712	166437	-0.19	-0.11	-8.00
Breda	100627	98569	100919	92199	-2.05	0.29	-8.38
Total	**3627126**	**3649173**	**3669473**	**3383953**	**0.61**	**1.17**	**-6.70**
Luxembourg							
Luxembourg	72968	72346	72812	67301	-0.85	-0.21	-7.77
Total	**72968**	**72346**	**72812**	**67301**	**-0.85**	**-0.21**	**-7.77**
Belgium							
Antwerp	1892914	2204649	2120240	2020932	16.47	12.01	6.76
Brussels	276674	308992	309612	286145	11.68	11.90	3.42
Liege	784778	778060	781582	715716	-0.86	-0.41	-8.80
Gent	2135780	2145314	2145470	1966349	0.45	0.45	-7.93
Total	**5090146**	**5437015**	**5356904**	**4989142**	**6.81**	**5.24**	**-1.98**

Table 7. The statistical indicators M and MA concerning the results in Tables 5 and 6

Country	*NN(BP) model*		*NN(GA) model*		*Logit model*	
	M	***MA***	*M*	***MA***	*M*	***MA***
Denmark	0.51	**0.56**	0.73	**0.73**	-1.70	**2.45**
Greece	-5.79	**5.79**	-0.95	**1.07**	2.96	**2.96**
Italy	-3.33	**3.34**	0.12	**0.50**	-2.43	**3.69**
Ireland	-0.46	**0.46**	-0.24	**0.24**	0.62	**0.62**
UK	-1.01	**1.01**	0.04	**0.04**	-1.81	**1.81**
Spain	1.25	**7.43**	4.04	**5.87**	3.69	**6.93**
Portugal	0.19	**2.01**	0.77	**1.49**	3.46	**3.46**
Holland	0.29	**2.35**	1.15	**1.38**	-6.72	**7.53**
Luxembourg	-0.85	**0.85**	-0.21	**0.21**	-7.77	**7.77**
Belgium	6.93	**7.36**	5.99	**6.19**	-1.64	**6.73**

M = mean value of the variations from the real data
MA = mean value of the absolute variations from the real data

We outline here that the road mode has been examined, since it represents the highest percentage of freight flows (82%) in comparison to the rail mode. For this reason – as well as for the well-known problems of congestion and environmental externalities of European road – the policy scenarios / sensitivity analyses have been focused on road transport. Clearly, it may now be interesting to show the impacts of this 'category' of distinct regions by changing the transport cost and time cost for the road mode (see next section).

4.4 Scenario Analysis for the European Transport Network

As already mentioned, freight transport causes high social costs, which in principle would have to be charged to the transportation sector. At present, because of severe problems such as congestion on the road transport network, the 'European regulation' has set a goal to reduce the road usage by imposing policy measures that serve to increase the cost of road usage (see Verhoef, 1996).

We will now investigate the consequences of varying the transportation costs and time costs for freight flows. A sensitivity analysis of the previous results based on some economic scenarios will now be carried out in this section by using again both the binary logit model and the NN(GA) model. We have 'chosen' the model B (NN(GA) model) since it offer the best performance in the learning phase (see again Tables 1-7). Several economic scenarios will be used (see for an overview, Table 8); and they will be concisely discussed here. Later, we will present the results related to the sensitivity analysis for the logit and the NN(GA) approach.

Table 8. The scenarios adopted

SCENARIO 1 : the transport cost for the road mode is increased by 15%;
SCENARIO 2 : the time cost for the road mode is increased by 15%;
SCENARIO 3 : the transport cost and time cost for the road mode is increased by 15%;

SCENARIO 4 : the transport cost for the road mode is decreased by 15%;
SCENARIO 5 : the time cost for the road mode is decreased by 15%;

SCENARIO 6 : the transport cost and time cost for the rode mode is increased by 15% and decreased by 15%, respectively.

In *Scenario 1* we assume that a uniform European tax policy for freight transport is adopted and that the cost attribute related to the road mode is increased by 15% for all links (ij). *Scenario 2* considers an increase of time cost by 15% as a result of the congestion problem, especially on long distance transport networks for freight transport. Thirdly, we assume an increase of both transport cost and time cost by

15% (*Scenario 3*). Furthermore, it may also be interesting to highlight the results by offering new future perspectives, based e.g. on objectives of the European Common Transport Policy (CTP) (see Rienstra,1998):

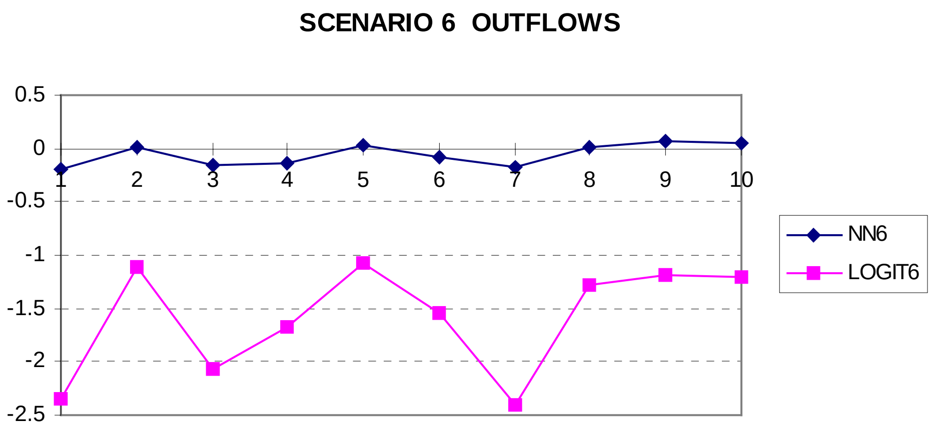
- free movement of goods and persons throughout the Union;
- elimination of unnecessary regulatory obstacles;
- economic cohesion and development among peripheral regions with the central region of the Union;
- encouraging social cohesion.

In this context it may also be useful to develop different policy scenarios in order to simulate alternative futures. In the light of the previous mentioned issues, we first assume a decrease of transport cost and time cost by 15% (*Scenarios 4 and 5,* respectively) for the road mode. Next we consider a new scenario (*Scenario 6*) where the transport cost and time cost for the road mode is increased by 15% and decreased by 15%, respectively, to give contrasting views of future policy scenarios.

The results of the scenarios adopted (the sensitivity analysis) are presented in Figures 2 and 3 (outflows and inflows, respectively) for the NN(GA) and the binary logit model. More precisely, these figures show the *relative variation* (defined as the difference between the predicted flow and the estimated flow as a percentage of the estimated flow). From these diagrams we can notice that the binary logit model is relatively more sensitive to changes in the attributes (transport cost and time cost) than the NN(GA) model, even though it can be argued that the behaviour / predictive ability of the models adopted appears to be roughly the same. For the sake of illustration, the results of *Scenario 6* on a country basis are mapped out in Figure 4. This figure demonstrates a similarity in overall patterns of the outflows and inflows for the NN(GA) and logit models.

It should also be noted that in *Scenario 6* (see Figure 4), even though the behaviour of both models is apparently the same, the core regions' behaviour - after an increase of transport cost by 15% and a decrease of the time cost by 15% - is opposite to that of the periphery in the two models. In other words - concerning *Scenario 6* - the NN(GA) model predicts an increase of transport flows only for the core regions; whereas the binary logit model shows a decrease of transport flows for all regions under analysis (see again Figure 4). Furthermore, we can observe that - in the logit analysis - the percentage variations for the core regions are lower than those in the peripheral regions. It addition, the NN(GA) model shows that the core regions are more sensitive to a decrease in the time cost than to an increase in the transport cost, while - as already underlined - the logit model presents - for each scenario - a substantial difference between the values of core and peripheral regions.

It would certainly be relevant to compare these results with those emerging from more recent data in order to better evaluate the predictive ability of the two models B and C. However, in the absence of updated data and given the good performance of the calibration / test phase (see Table 1), the above results may be considered valid and relevant. Moreover, these results may offer a 'range of values' to policy actors aiming to evaluate the impact of cost changes on flows, given the intrinsic limits of both adopted models. On the one hand, the large amount of data at an aggregate level hampers a behavioural perspective inherent in logit models. On the other hand, the type of architecture adopted in NN models seems critical for the validity of the results. Consequently, the results of our model may be used as a benchmark for the results of other models, by offering a more 'flexible' output to policy actors.



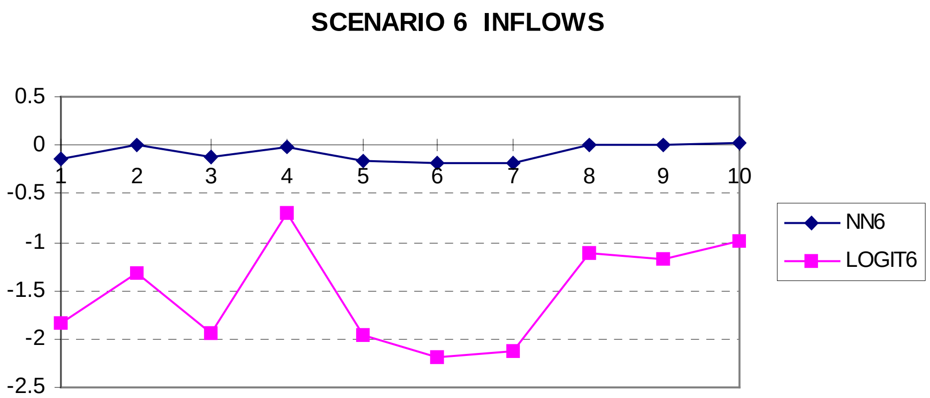


Figure 4. The prediction results of the outflows and inflows of the chosen models in Scenario 6 (y-axis: relative variation; x-axis: the ten European countries under consideration; see Figure 1 for the related countries' legend)

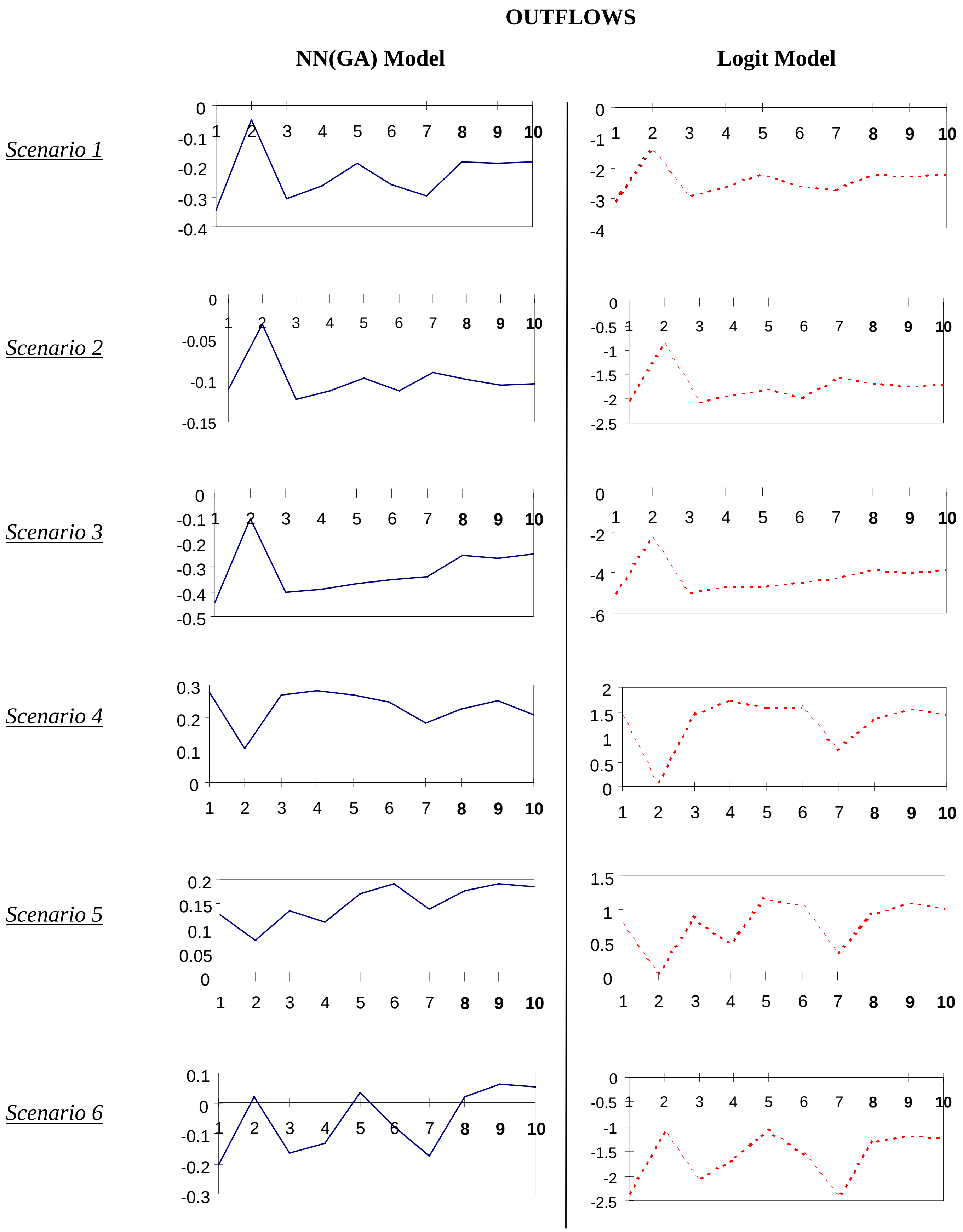


Figure 2. The results of the sensitivity analysis for the outflows (y-axis:relative variation; x-asis: the ten European countries under consideration; see Figure 1 for the related countries' legend)

INFLOWS

NN(GA) Model **Logit Model**

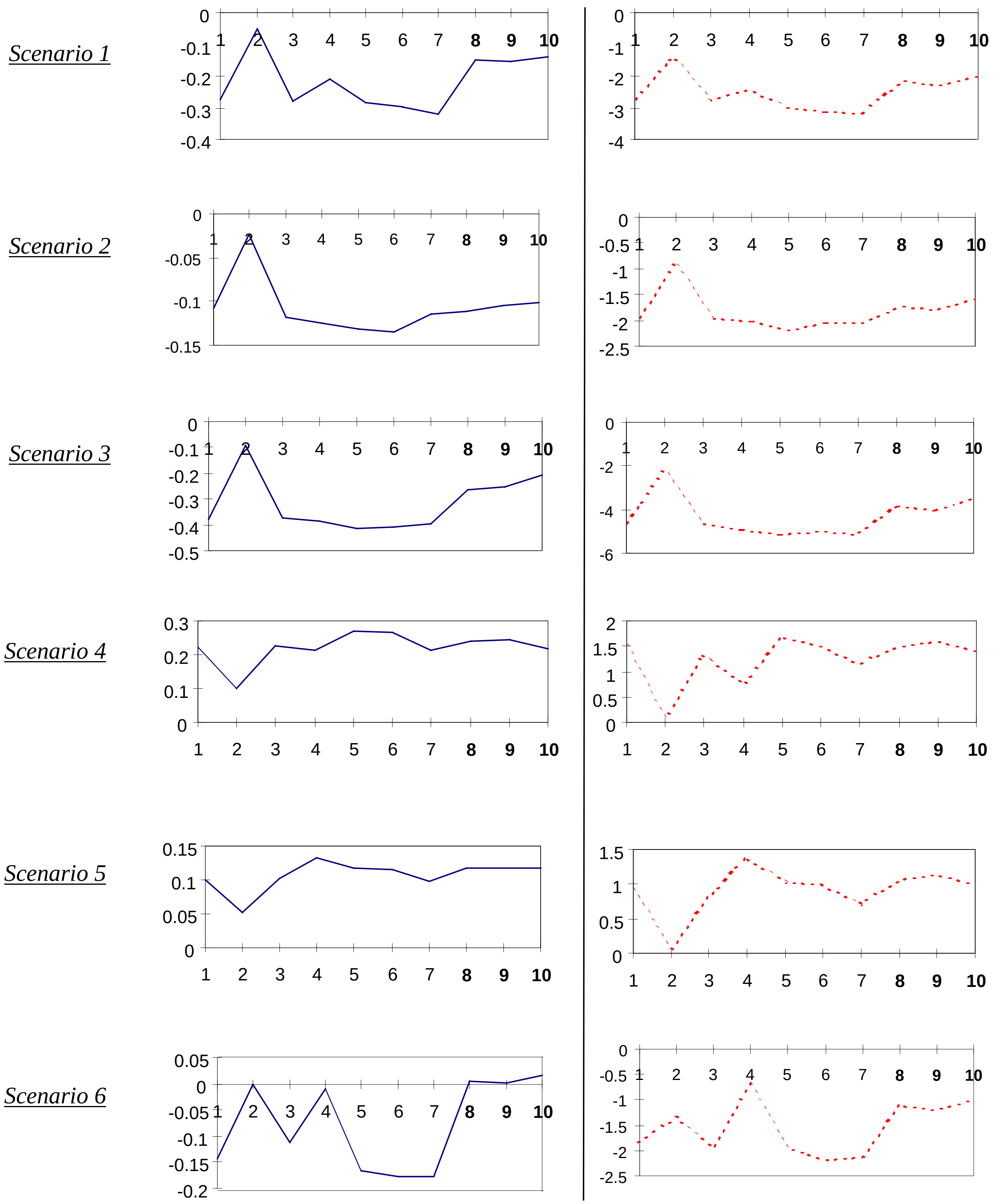


Figure 3. The results of the sensitivity analysis for the inflows (y-axis: relative variation; x-asis: the ten European countries under consideration; see Figure 1 for the related countries' legend)

4.5 Concluding Remarks

The conclusion for the above experiments is interesting in that the combined approach 'NN(GA)' can certainly be considered as a valid tool for *spatial forecasting*. Concerning the issue of *temporal forecasting* we should be more cautions, given the absence of updated data.

In general, the previous results create quite confidence, also in absence of updated data, given the 'good' results in the learning /calibration phase.

5. EPILOGUE

This paper has explored the use of evolutionary computation (and particularly of GAs combined with NNs) meant to measure 'evolutionary activity', i.e the 'spontaneous generation of innovative functional structures' (see Bedan and Packard 1992). Like connectionism (i.e. the study of computer programmes inspired by neural systems), evolutionary computation is a 'bottom-up' paradigm in which humans write only very simple rules, while complex behaviour emerges from the massive parallel application and interaction of these simple rules. However, whereas in connectionism these rules are typically based on simple 'neural' thresholds, i.e., the activation and strength of connections, in evolutionary computation the rules are 'natural selection' with variation due to crossover and/or mutation (see again Mitchell 1996).

Evolution may in general be regarded as a method for designing innovative solutions to complex problems, inspiring computational search methods based on the simple rules in which the 'fittest' solution tends to survive and reproduce. Thus for the analysis of complex behaviour EAs seem to offer a great perspective.

From a social science perspective it is also interesting to investigate whether the above described selection process can be interpreted in terms of a utility maximisation process (or, in general, as a behavioural paradigm; see e.g., Ben-Akiva and Lerman, 1985). To answer this question further research would be needed on the theoretical compatibility between EAs and utility maximising (behavioural) models (such as logit models), as well as between EAs and NNs. This is a particularly intriguing issue in light of some recent studies which aim to offer also a 'behavioural' framework for NNs (see Sections 2 and 3). In this context, Fischer and Leung (1998) argue that "*Neural spatial interaction models are termed neural in the sense that they have been inspired by neuroscience. But they are more closely related to conventional spatial interaction models of the gravity type than they are to neurobiological models. They are special classes of general feedforward neural network models...*"

In future research it would be interesting to investigate whether EAs may show a behavioural ‘compatibility’ with spatial interaction models (and consequently with logit models). We would then have to analyse under which conditions these 'conventional' models may be considered as a 'powerful' class of universal approximators for spatial/social interaction. Clearly, EAs may offer another interesting conceptual research question, viz. can natural selection be interpreted in the framework of economic utility theory? This issue is at present intensively discussed in evolutionary economics. Apart from further theoretical/methodological research, this would also require more rigorous empirical tests on real-word phenomena. Needless to say that evolutionary analysis opens a wide array of new research challenges.

ACKNOWLEDGMENTS

The second author gratefully acknowledges the Italian CNR Project PFT2 n. 97.000264.PTF77 as well as the MPI project 40%. The authors also thank NEA Transport Research and Training, Rijswijk – The Netherlands, for proving the extensive data set.

REFERENCES

Bedan M. A. and N. H. Packard (1992). Measurement of Evolutionary Activity, Teleology and Life. In: *Artificial Life II* (C.G. Langton, C.Taylor, J.D. Farmer, and S.R. Rasmussen ,eds.), Addison Wesley, Reading, MA.

Ben-Akiva M. and S. R. Lerman (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press, Cambridge, Massachusetts.

Bertoni A. and M. Dorigo (1992). *Implicit Parallelism in Genetic Algorithms*, Technical Report, 92-102, Dipartimento di Elettronica, Politecnico di Milano.

Colorni A., M. Dorigo and V. Maniezzo (1992a). ALGODESK: An Experimental Comparison of Eight Evolutionary Heuristic Applied to the AQP Problem. *European Journal of Operational Research.*

Colorni A., M. Dorigo, and V. Maniezzo (1992b). Scheduling School Teachers by Genetic Algorithms. In: *Combinatorial Optimization, New Frontiers in Theory and Practice* (M. Akgul, H.W. Hamacher and S. Tfekci, eds.), NATO ASI Series, Series F, Vol. 82, Springer-Verlag, Berlin.

Colorni A., M. Dorigo, and V. Maniezzo (1994). Introduzione agli Algoritmi Naturali, *Rivista di Informatica*, 3, pp. 179-197.

De Jong K.A. (1975). *Analysis of the Behavior of a Class of Genetic Adaptive System*, Ph.D. dissertation, Univ. of Michigan.

Dorigo M. and V. Maniezzo (1992). Parallel Genetic Algorithms: Introduction and Overview of Current Research. In: *Parallel Genetic Algorithms: Theory and Applications* (J. Stenders ,ed.), IOS Press, Amsterdam.

Fischer M. M. and S. Gopal (1994). Artificial Neural Networks: A New Approach to Modelling Inter-regional Telecommunication Flows, *Journal of Regional Science*, 34, 503-527.

Fischer M.M. and Y. Leung, (1998). A Genetic-Algorithms Based Evolutionary Computational Neural Network for Modelling Spatial Interaction Data, *The Annals of Regional Science*, (forthcoming).

Goldberg D.E. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison Wesley, Reading, MA.

Himanen V., P. Nijkamp and A. Reggiani (eds.) (1998). *Neural Networks in Transport Applications*, Avebury, Aldershot.

Holland J.H. (1975). *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor.

Kosko B. (1992). *Neural Networks and Fuzzy Systems*, Prentice Hall Inc., Englewood Cliffs, N.J.

Maniezzo V. (1994). Genetic Evolution of the Topology and Weight Distribution of Neural Networks. In: *Proceedings of the IEEE International Conference on Transactions on Neural Networks*, 5, 1, IEEE Computer Society Press, pp. 39-53.

Maren C., A. Harston and R. Pap (1990). *Handbook of Neural computing Application*, Academic Press, San Diego.

Mitchell M. (1986). *An Introduction to Genetic Algorithms*, The MIT Press, Cambridge, MA.

Muhlenbein H. (1989). Parallel Genetic Algorithms, Population Genetic and Combinatorial Optimization. In: *Proceedings of the Third International Conference on Genetic Algorithms* (J.D. Schaffer, ed.), Morgan Kaufmann, San Mateo, CA., pp. 416-421.

Nijkamp P. and A. Reggiani (1996). Modelling Network Synergy: Static and Dynamic Aspects, *Journal of Scientific & Industrial Research*, 55, 5, pp.931-941.

Nijkamp P. and A. Reggiani (1998). *The Economics of Complex Spatial Systems*, Elsevier, Amsterdam.

Nijkamp P., A. Reggiani and T. Tritapepe (1996). Modelling Inter-Urban Transport Flows in Italy: A Comparison between Neural Network Approach and Logit Analysis, *Transportation Research C*, 4, 323-338.

Nijkamp P., A. Reggiani and T. Tritapepe (1997). Analysis of Complex Networks: An Overview of Methodologies and a Neural Network Application to Intermodal Transport in Italy. In: *Policy Aspect of Networks* (C. Capineri and P. Rietveld, eds.) Ashgate, Aldershot, pp.285-305.

Reggiani, A., R. Romanelli, T. Tritapepe and P.Nijkamp (1998a). Neural Networks: An Overview and Applications in the Space Economy. In: *Neural Networks in Transport Applications* (V. Himanen, P. Nijkamp and A. Reggiani, eds.), Avebury, Aldershot (forthcoming).

Reggiani, A., P. Nijkamp and W.-F. Tsang (1998b). European Freight Transport Analysis Using Neural Networks and Logit Models. In: *Accessibility, Trade and Locational Behaviour* (A. Reggiani, ed.), Avebury, Aldershot (forthcoming).

Reggiani, A., P. Nijkamp and E. Sabella (1998c). Evolutionary Neural Network for European Freight Transport Modelling, Discussion Paper, Tinbergen Institute, Amsterdam.

Rienstra S.A., *Options and Barriers for Sustainable Transport Policies. A Scenario Approach*, Netherlands Economic Institute (NEI), Rotterdam.

Rumelhart D.E., G.E. Hinton and R.J. Williams (1986). Learning Internal Representation by Error Propagation. In: *Parallel Distributed Processing: Explorations in the Microstructure of Cognition* (D.E. Rumelhart and J.L. McClelland, eds.), MIT Press, Cambridge, MA.

Schintler L. A. and O. Olurotimi (1998). Neural Networks as Adaptive Logit Models. In: *Neural Networks in Transport Applications* (V. Himanen, P. Nijkamp and A. Reggiani Eds.), Avebury, Aldershot (forthcoming).

Verhoef E. T. (1996). *The Economics of Regulating Road Transport*, Edward Elgar, Aldershot.